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Efficient Deep Transfer-Based Ensemble System for Robust Kidney Stone Identification

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Abstract: Chronic kidney disease is a major health problem across the world, and kidney stones are a prevalent illness that makes the kidneys work less well. Because kidney stone disorders don't show any symptoms, it's very important to find them early and accurately to avoid serious problems. This work uses datasets, Kidney data and CT Kidney Stone data, and innovative methods including Relief for feature selection and KNN with k-Fold validation for classification to improve the accuracy of diagnoses. For both classification and detection tasks, a group of deep neural networks and designs based on transfer learning have been used. The suggested method is quite accurate, as shown by the classification results, which reveal that Xception got 100% accuracy on the CT Kidney Stone data and 98% on the Kidney data. YOLOv5s6 has a mean average Precision (MAP) of 87% across both datasets, which shows that it works well for detection. These findings show that combining inductive transfer-based ensemble DL with optimal feature selection is a good way to find kidney stones quickly and reliably. This might help improve early diagnosis and patient outcomes.

*“**Index Terms** -Deep learning, computed tomography, kidney stone, transfer learning, ensemble network, Xception, Classification and Detection”.*

1. INTRODUCTION

Kidney illnesses are a major health problem across the globe that may affect people of all ages and genders. The early detection of kidney problems is very essential as they can eventually get aggravated and is also capable of killing you. One of the most severe diseases that can impair the functioning of kidneys is kidney stones. It is good to identify and locate the stones within the kidney earlier so that they do not develop into chronic kidney complications. Diagnosis of small kidney stones in their initial stages can significantly reduce chances of the development of more severe complications on the kidneys. Nonetheless, the population of kidney patients all over the world had been continually increasing and the third-world countries are also deficient in nephrologists [1]. This makes it such that a lot of individuals who have kidney issues never receive proper care at the correct moment, and so the presence of fast and efficient screening devices is paramount.

Routine methods of medical imaging such as ultrasonography, and a scanning process known as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are also common among kidney problems checking techniques. These procedures are time consuming to doctors and the anxiety to handle many patients may cause wrong diagnosis [2]. In addition, the insufficiency of nephrologists may lead to a significant delay in treatment, which complicates the outcomes of patients. To overcome the problems, computer-aided medical interventions have found a convenient means of assisting in detecting and diagnosing kidney disorders at an early stage. These computerized technologies simplify the work of doctors and reduce the possible error of a human being, resulting in better and unbiased diagnosis [3].

The issue of artificial intelligence (AI) has been developed significantly in the recent past years and it has resulted in the development of automated therapies in various medical illnesses including breast, lung and heart disorders. Although this is a step towards the right direction, still, renal problems are not studied to the extent yet. Machine applications are interested in creating autonomous models that will properly identify kidney diseases and thus assist physicians in treating their patients with appropriate treatment at the opportune moment [4]. The use of CT imaging to locate, quantitate and distinguish kidney stones has been commonplace. The field of study on medical imaging detection is large and there is potential in identifying medical images using the medical models of deep learning (DL) and machine learning (ML) [5].

The intention of the proposed research is to improve the current progress and use combinations of inductive transfer-based ensemble classifier known as the use of inductive transfer-based deep learning ensemble networks, or deep neural networks (DNNs) and machine learning (ML) to learn the functions. These are supposed to rapidly identify features in CT images of kidneys and make use of the most ideal sections of ensemble learning in order to ensure that the accuracy of diagnoses is made. The aim of this system is to assist medical practitioners with Automatic detection and diagnosis of kidney stones. It will assist in solving the increasing cases of kidney diseases.

2. RELATED WORK

During the past several years, much was studied on the modes of how the kidney stones can be searched and categorized. Much of this has been done regarding how to unite advanced “machine learning (ML) and deep learning (DL)” methods with medical imaging methods. These papers indicate the necessity of precise and automated instruments to assist in diagnosing and treatment of kidney stones.

Serrat et al. [6] have developed MyStone system aimed to automatically classify kidney stones in categories based on the use of sophisticated algorithms on medical images. Not bad was the algorithm that was used precisely sorting the stones by some specific releases that were withdrawn within imaging data. The fact that their model involves employing advanced methods indicates how advanced solutions can simplify complex diagnostic processes.

Martinez et al. [7] proposed an automated method to classify the kidney stone images generated during ureteroscopy with the help of ensemble learnings. They also improved the accuracy of categorization very much, using as many models as possible in a given framework. Ensemble learning is ideal in compensating the incompetencies of individual models hence enhancing the performance of the classification system.

Verma et al. [8] considered the way to use, to detect kidney stones, k-Nearest neighbors (KNN) and support Vector Machines (SVM). They found it in their research that the classical ML models can potentially be used to effectively distinguish between several types of stones. The study emphasized on the significance of selecting appropriate classification techniques on each imaging data set since these models relied on varying procedures extracted the features to achieve high accuracy.

Employed radiomics and ML, De Perrot et al. [9] examined the way in which it is possible to distinguish between kidney stones and phleboliths on the basis of low-dose CT scans. They employed advanced feature elimination and examination strategies to ensure that the distinctions were evident, and this is significantly important in diminishing diagnostic errors. The study reveals that radiomics, the scientific technique of obtaining quantitative information out of medical imaging, is growing increasingly significant to be used as a diagnostic methodology.

Aksakalli et al. [10] considered the possibility of using both the ML and DL algorithms to classify kidney stones in X-rays images. They found using DL models to be superior to the common ML methods in handling complex imaging data. The proposed approach had superior scores with the more complex use of “convolutional neural networks (CNNs)”. This indicates that the ability of the additive learning models to establish complex patterns in medical photos.

An article by Manoj et al. [11] discussed a study that involved the use of DL models in locating kidney stones automatically. Their research concerned nothing but elevating DL strains of the specific task of locating kidney stones and they could increment the detection rates by large margins. The study suggests the imminence to tailor DL models to accommodate the particular characteristics of renal imaging data, so as to enhance the accuracy of predictions.

Caglayan et al. [12] developed the method of applying DL phenomenon to assist in the discovery of kidney stones in CT images. They applied a special type of a neural network architecture, which was implemented to address the issues that appear during the medical imaging experience, which include noise and varying resolution. The study revealed that DL could be of assistance to the doctors because it will automatically detect the diagnosis process making it the diagnosis quicker and more reliable.

The work of Li et al. [13] constructs deep segmentation networks that are capable of identifying kidneys and kidney stones in CT scans of abdomen CT volumetric data that have not been enhanced. They integrated the tasks of segmentation and detection in their system and hence it became possible to conduct the complete study on the CT images. Their study was addressing the issues associated with low-contrast imaging data by focusing on non-enhanced images. This was evidence that DL models are very flexible in terms of handling various imaging scenarios.

Overall, these studies indicate how the ML and DL methods have facilitated the process of identifying and categorizing kidney stones. They emphasize the significance when it is necessary to find the way how to enhance the accuracy of diagnosing with the help of extraction of features, fine-tuning models, and tailoring of datasets to specific tasks. It is also clear with the application of ensemble learning as demonstrated by Martinez et al. [7] how the combination of models can be used to getaly overcome their respective shortcomings. Similarly, the application of radiomics in research works, such as that of De Perrot et al. [9], indicates how quantitative data of imaging could enhance diagnostic aptitudes.

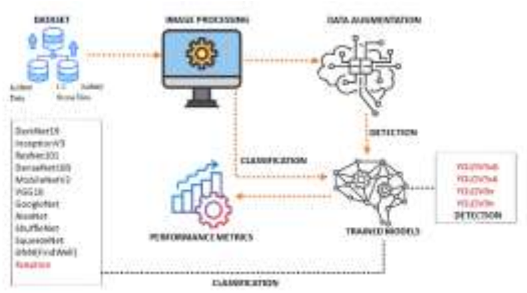
Verma et al. [8] mentioned that such ML models as KNN and SVM have demonstrated their potential but the studies by Aksakalli et al. [10] and Manoj et al. [11] indicate that DL archetypes are more effective, so we should shift toward more elegant models. Deep feature extraction and learning are applied in these methods to examine the complex medical images, hence they are better and consistent.

Furthermore, as demonstrated by Martinez et al. [7], the matter of combining the strengths of various models exists because the approach of ensembling learning frameworks is a fair one. This particularly matters in the field of medicine where accuracy and reliability are of great concern. Segmentation-based methods [13] developed by Li et al. offer an additional scope of accuracy, as they combine numerous diagnosis tasks into a single framework.

The study also talks about the problems that come with finding kidney stones, such how different imaging methods (CT, X-ray, ultra sound) might show different types of stones and how vital it is to have high-resolution and low-noise data. Researchers like Caglayan et al. [12] and Serrat et al. [6] have dealt with these problems by making their models work with the unique details of renal imaging datasets.

3. MATERIALS AND METHODS

The proposed system applies inductive transfer-based deep neural networks ensembles in detecting kidney stones in a manner that is effective and robust. It achieves this through a fancy classification and detection algorithm and feature selection technique. Many different deep learning models are deployed to accomplish the categorization goal including the DarkNet19 [17], InceptionV3, ResNet101, DenseNet169 [16], MobileNetV2 [15], VGG16, GoogleNet [14], AlexNet [14], ShuffleNet, SqueezeNet, and Xception. ReliefF [19]" is used to improve feature extraction and selection, while KNN uses k-Fold validation to improve the accuracy of predictions. To find kidney stones, the most advanced models, such "YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n", are used. This makes sure that the stones are found correctly. The system is meant to look at data from sets: Kidney data and CT Kidney Stone data [18]. Its main goal is to combine feature selection methods with deep learning models to make the system more accurate and efficient. Thus ensemble architecture is meant to be a reliable and scalable way to find kidney stones early on, as the ailment doesn't always show symptoms and thus lowers the chance of health problems.

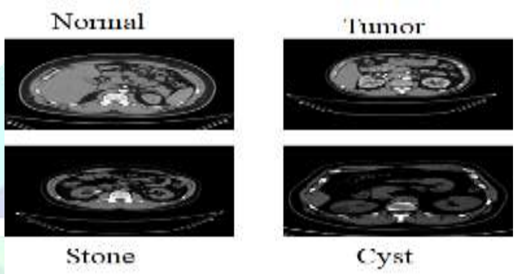


"Fig.1 Proposed Architecture"

The system architecture (fig. 1) uses a dataset of Kidney data and CT Kidney Stone data [18], which has been pre-processed and added to in order to improve the training data. Then, this information is put into different deep learning models to do tasks like categorization and detection. We use performance measurements to see how well these models work. You may utilize the trained models for more things in medical imaging.

i) Dataset Collection:

The collection of datasets comprises two important ones: the Kidney data and the CT Kidney Stone data [18]. The Kidney data includes several kidney diseases, and the CT Kidney Stone data has labeled CT scans that are grouped into normal, Tumor, Stone, and Cyst classifications. This Kaggle dataset is meant to be used for medical picture classification and diagnosis. Its purpose is to employ machine learning and image processing methods to make it easier to find kidney disease. The dataset has a lot of different pictures that may be used to train models.



"Fig.2 Dataset Images"

ii) Pre-Processing:

We get the dataset ready for modeling in the pre-processing stage. This involves processing images and adding more data to ensure the prediction model gets input.

a) Image Processing:

For Classification: there are various phases in the picture preparation for classification that improve the quality and variety of the images. The image data Generator changes the size of photos to make them normal, shears them to change their shape, and zooms them in to make them seem bigger. To provide diversity, photographs are flipped horizontally, and they are all resized to the same size so that they work with the model. To extract features, CNN and HOG models are used. First, the photos are read and resized, and then the colors are changed. The picture data and labels are added together and then turned into numpy arrays so that the model may handle them further.

For Detection: to start the preprocessing for detection, photos are turned into blob objects that may be used for detection tasks. We construct classes and draw bounding boxes around the items in the pictures that are important. After that, the picture array is changed into a numpy array so that it may be worked on further. You can load a pre-trained model by reading its network layers and getting the output layers. The annotation files are added to the picture, that is then changed from BGR to RGB, scaled, and a mask is made to show just the important parts.

b) Data Augmentation: To provide more data to detection, random changes are made to images to make the dataset more diverse. This involves rotating the pictures to make them seem like they are coming from various points and perspectives, as well as making additional changes to change things like size and position. These additions make the training set more varied, which makes the model better at generalizing and being more resilient for object identification tasks.

iii) Algorithms:

For Classification:

DarkNet19: A lightweight, high-performance “convolutional neural network (CNN)” that is good at detecting objects and is built for quick inference while still being able to classify things with high accuracy [17].

InceptionV3: InceptionV3 is a deep convolutional neural network that is noted for its economical architecture. It combines several filter sizes in each layer, which makes picture categorization more accurate and less computationally difficult.

ResNet101: A deep residual network with 101 layers that uses skip connections to stop gradients from disappearing. This makes it very good at training deep networks for hard classification problems.

DenseNet169: A convolutional neural network with layers that are all connected to each other. This makes sure that gradients flow smoothly, features may be reused, and image classification tasks function better [16].

MobileNetV2: A convolutional neural network that works well on mobile devices and is tailored for real-time use. It focuses on reducing computation and model size while keeping accuracy in classification tasks [15].

VGG16: A deep convolutional network with 16 layers is popular for image classification since it is simple and efficient. It does this by stacking many convolutional layers on top of fully connected layers.

GoogleNet: A deep convolutional network that employs inception modules to integrate different sizes of convolution filters. This lets it learn complicated features while still being able to do large-scale classification quickly [14].

AlexNet: one of the first deep neural networks to use ReLU activation, dropout, and data augmentation to achieve big performance improvements on big picture datasets [14].

ShuffleNet: A small neural network designed for mobile devices that uses channel shuffle operations to make calculations faster while keeping good performance in classification tests.

SqueezeNet: A deep neural network that is very small and can reach AlexNet-level accuracy with less parameters. This makes it perfect for use in places where resources are limited.

DNN (FindWell): A special type of neural network, a deep neural network (DNN), optimized to certain disciplines with complex layers and techniques to rapidly examine and classify image data. It is applicable with medical and other specialty dataset [15].

Xception: A potentially advanced deep learning architecture based on the Inception one, but normal convolution layers are removed and replaced with depthwise separable convolutions. This improves the classification of pictures very well.

For Detection:

YOLOV5x6: Fine-tuned representation of an advanced object identification model of the family of the YOLO models (YOLO which is You only look once) and is developed with the view of detecting things in real-time video or picture information data as fast and accurately as possible.

YOLOV5s6: The YOLO v5x6 is upgraded to a lighter version and is more efficient, thus can operate faster using smaller processing power. It is therefore ideal to the type of mobile and edge device that requires identification of objects.

YOLOV8n: YOLO model is an enhanced model with emphasis on speed and accuracy. It is able to detect the objects in diverse settings and is more efficient and effective as compared to the previous versions.

YOLOV9n: YOLO is the latest improved version that performs even superiorly than its predecessors, as it has real-time object-detection provided that it exhibits an enhanced performance and identification capability on difficult detection duties due to its improved speed and accuracy.

4. RESULTS & DISCUSSION

Accuracy: A test is valid when it is able to distinguish correctly the differences between the sick and healthy individuals. We ought to determine the percentage of true positives and true negatives within all the cases that were tested to gain a concept of the degree of accuracy of the test. This could be put in math terms as:

$$"Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} (1)"$$

Precision: A test is valid in that it can and is capable of identifying the differences between the sick and healthy persons. We should establish the proportion of true positives and true negatives among all the cases which were tested to get some idea of the extent of accuracy of the test. This may be written in mathematical language as:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)"$$

Recall: In ML, recall stands as an indicator of how successfully a model identifies all instances of a particular class. it is the proportion of the numbers of correct positive chaque in a model to the total number of positive chaque. This will give you a clue of the extent to which a model represents all the instances of a particular class.

$$"Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (3)"$$

F1-Score: The F1 score is the measurement of the accuracy of a ML model. It takes the accuracy and recall result of a model and merges them. The accuracy statistic records the number of times a model gave a valid prediction over the entire dataset.

$$"F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100(1)"$$

MAP: Goodness of ranking- Measure of how good a ranking is called, Mean Average Precision (MAP). It checks the number of useful suggestions and their placement in the succession. And the column entry at k, the mean of the mean Precision (AP) at k over all users or all queries.

$$"mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k (5)"$$

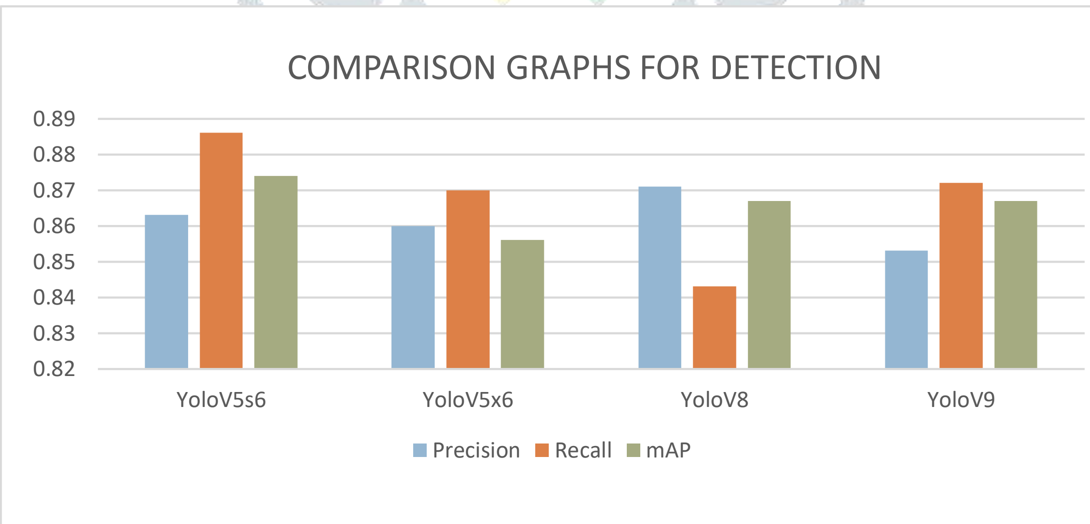
In Table (1), check the performance metrics for each algorithm, such as accuracy, recall, and mAP. The YOLOV5s6 always does better than all other algorithms on all criteria. The tables also show how the metrics for the different algorithms compare to each other.

In Table (2 & 3), look at the performance metrics for each method, such as “accuracy, precision, recall, and F1-score”. The Xception always does better than all the other algorithms on all criteria. The tables also show how the metrics for the different algorithms compare to each other.

“Table.1 Performance Evaluation Metrics for Detection”

Model	Precision	Recall	mAP
YoloV5s6	**0.863**	**0.886**	**0.874**
YoloV5x6	0.860	0.870	0.856
YoloV8	0.871	0.843	0.867
YoloV9	0.853	0.872	0.867

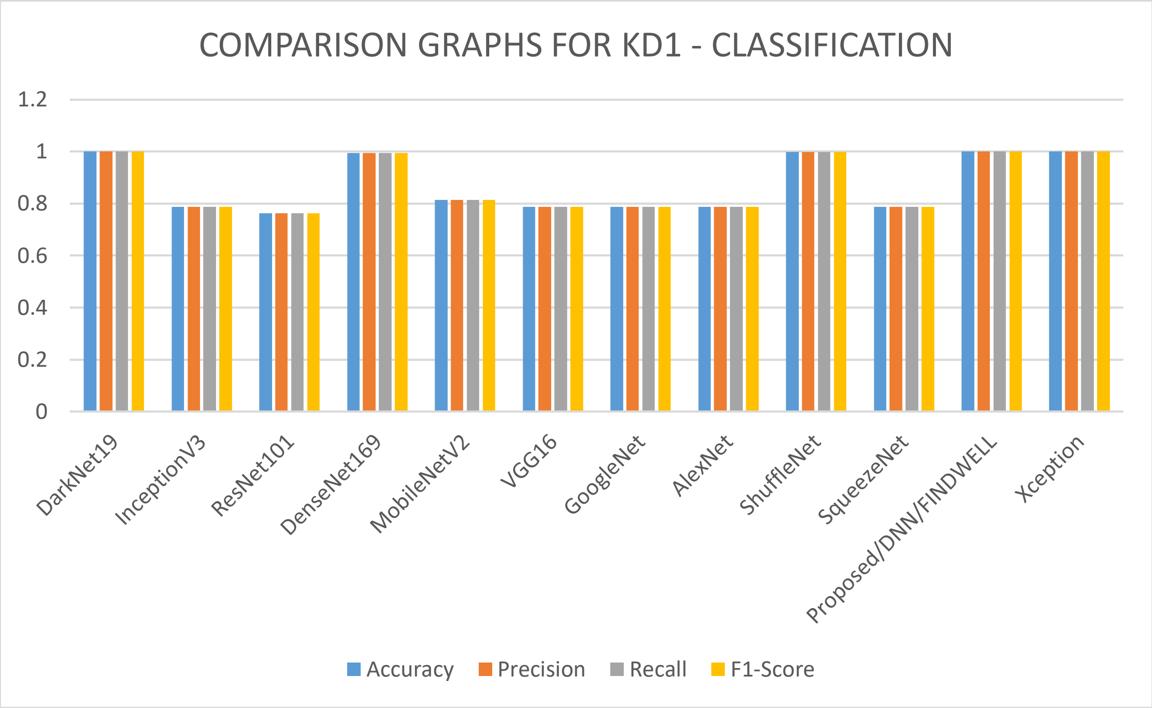
“Graph.1 Comparison Graphs for Detection”



“Table.2 Performance Evaluation Metrics for KD1 – Classification (CT Kidney Stone)”

Model	Accuracy	Precision	Recall	F1-Score
DarkNet19	1.000	1.000	1.000	1.000
InceptionV3	0.787	0.787	0.787	0.787
ResNet101	0.762	0.762	0.762	0.762
DenseNet169	0.995	0.995	0.995	0.995
MobileNetV2	0.814	0.814	0.814	0.814
VGG16	0.787	0.787	0.787	0.787
GoogleNet	0.787	0.787	0.787	0.787
AlexNet	0.787	0.787	0.787	0.787
ShuffleNet	0.999	0.999	0.999	0.999
SqueezeNet	0.787	0.787	0.787	0.787
Proposed/DNN/FINDWELL	1.000	1.000	1.000	1.000
Xception	**1.000**	**1.000**	**1.000**	**1.000**

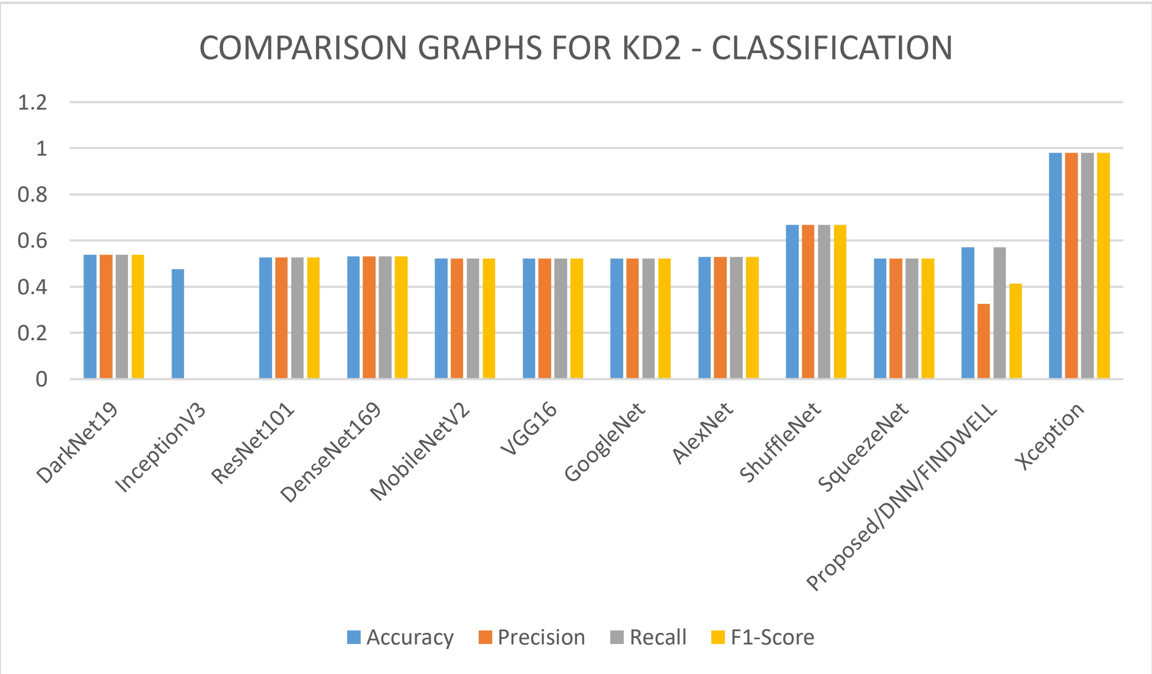
"Graph.2 Comparison Graphs for KD1 – Classification (CT Kidney Stone)"



"Table.3 Performance Evaluation Metrics for KD2 – Classification"

Model	Accuracy	Precision	Recall	F1-Score
DarkNet19	0.538	0.538	0.538	0.538
InceptionV3	0.477	NaN	NaN	NaN
ResNet101	0.526	0.526	0.526	0.526
DenseNet169	0.532	0.532	0.532	0.532
MobileNetV2	0.523	0.523	0.523	0.523
VGG16	0.523	0.523	0.523	0.523
GoogleNet	0.523	0.523	0.523	0.523
AlexNet	0.529	0.529	0.529	0.529
ShuffleNet	0.668	0.668	0.668	0.668
SqueezeNet	0.523	0.523	0.523	0.523
Proposed/DNN/FINDWELL	0.570	0.325	0.570	0.414
Xception	**0.980**	**0.980**	**0.980**	**0.980**

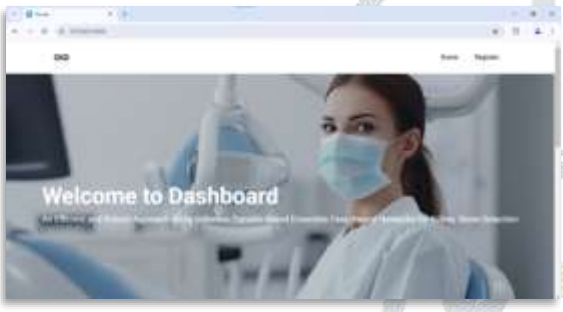
"Graph.3 Comparison Graphs for KD2 – Classification"



Graph (1) shows precision in Iceblue, recall in orange, and MAP in Olive green. The YOLOV5s6 outperforms all the other models on all measures, getting the top scores. The graphs above show these results in a way that is easy to see.

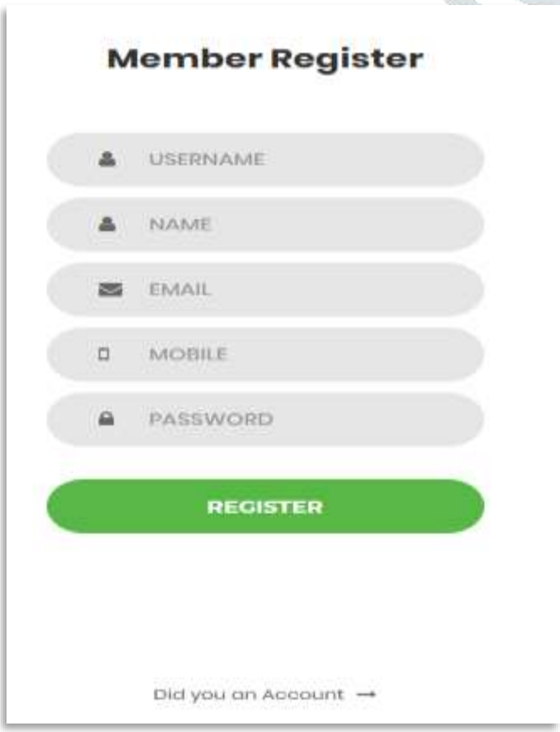
Graphs 2 and 3 show that accuracy is in light blue, precision is in orange, recall is in gray, and F1-score is in light yellow. The Xception outperforms all of the other models on all criteria, reaching the highest values. The graphs above show these results in a clear way.

“Fig.3 Dashboard”



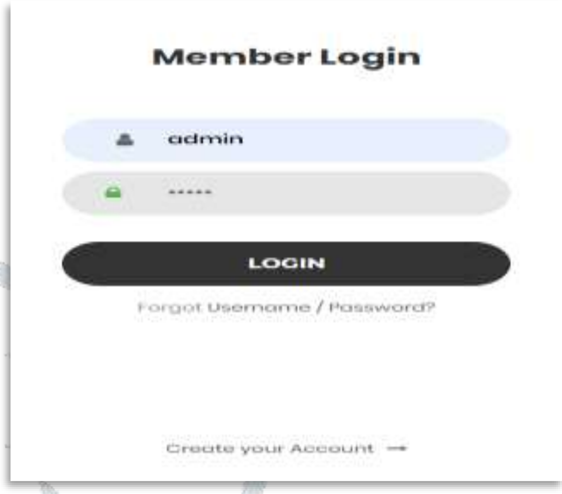
A medical dashboard online that uses deep learning to detect kidney stones. It shows a masked female doctor in a clinical situation.

“Fig.4 Register page”



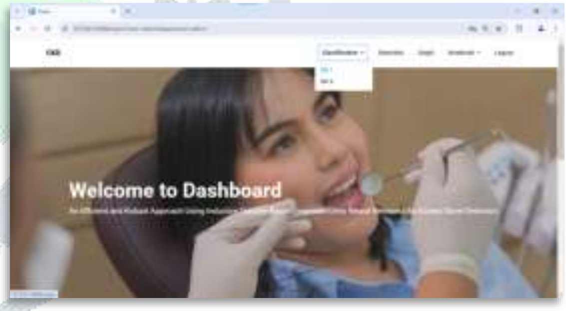
This is a "Member register" form with a green "register" button and spaces for a username, name, email, mobile number, and password.

“Fig.5 Login Page”



This is a "Member Login" form that has fields for a username and password, a "LOGIN" button, and links to recover an account or sign up.

“Fig.6 Welcome to Dashboard Classification of Dataset 1”



An online dashboard for finding kidney stones that has choices for categorization, detection, graphs, and notebooks, as well as an admin interface that requires a login.

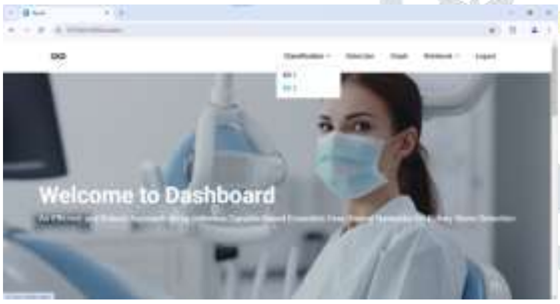
“Fig.7 Test Case 1”

This picture illustrates a web program for finding “CKD (chronic Kidney disease)” where a user may choose and submit medical photographs to be sorted.

“Fig.8 Results of Test case 1”

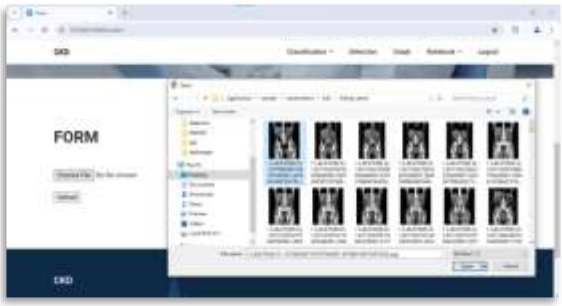
This picture shows the results of a kidney stone test. The CT scan is marked as "normal," which means that no kidney stones were found.

“Fig.9 Classification of Dataset 2”



This picture displays a web-based dashboard for finding kidney stones using deep learning. It has choices for classifying stones and a healthcare-themed backdrop.

“Fig.10 Test case 2”



This picture shows a web-based CKD detection form. The user chooses a CT scan image of a kidney stone for examination.

“Fig.11 Results of Test case 2”

A medical imaging scan of the abdomen that focuses on the kidneys, spine, and pelvis and shows possible kidney stones.

“Fig.12 Detection dashboard”

The title of the picture is "Welcome to Dashboard," and it depicts the dashboard interface of a web tool that helps find kidney stones.

“Fig.13 Test case 3”

An online program that lets you upload files to check for kidney stones. People may chose medical photographs and submit them for examination.

"Fig.14 Results of Test case 3"

It seems like this picture is a medical scan with a box around it that says "normal 0.91." This probably means that it is a categorization or detection result.

5. CONCLUSION

In conclusion, this research shows that sophisticated deep learning approaches and optimal feature selection methods are better at finding and classifying kidney stones. Using Relief [19] to choose features and KNN with k-Fold validation made the classification models much more accurate. Xception did the best job at classifying, with 100% accuracy on the CT Kidney Stone data [18] and 98% accuracy on the Kidney data. The YOLOv5s6 model did a great job at detecting tasks, with a mean average Precision (MAP) of 87% on both datasets. These results show that using ensemble deep learning models and transfer learning methods together is a good way to discover kidney stones quickly and accurately. This combination of these high-performance algorithms ensures that the result of diagnostic tests is accurate. This leaves room to develop automated systems which can be used to diagnose and treat kidney stone pathologies earlier by the health practitioners in the care. These results demonstrate that nephrologists could improve patient care and outcomes through the use of the most recent ML models.

These destiny objectives of the study include enhancing the performance of the model by including other data sources, e.g. ultrasound and MRI scans to ensure its wider usage. The possibility to recognize things in real time, to interface with medical imaging systems, and bettering rapid inference algorithms would all be able to increase speed of diagnosis. In addition, considering more advanced practices such as explainable AI could also make models more transparent, thereby assisting healthcare employees to accept automated inferences. It would be possible that by including additional patient demographics into the database, the model could be even more solid and helpful in a broader variety of treatment scenarios.

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